MULTIMODAL REGISTRATION OF THE FACE FOR COMPUTER-AIDED MAXILLOFACIAL SURGERY

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INTRODUCTION

Maxillofacial dysmorphosis of the lower part of the face (disequilibrium between the mandible, the upper jaw and the face) has important functional, orthodontic and aesthetic consequences : respiration difficulties, mastication and elocution troubles, disruptions of the dental occlusion, face asymmetry… Orthognathic surgery can correct these problems but is very delicate. It mainly consists in osteotomies and bone segment repositioning in order to realign the upper and lower jaws (Fig. 1). This surgery requires precise planning of bone structure displacements. One of the main request of the patients concerns the prediction of the face aesthetic after the operation.

A complete protocol for computer-aided maxillofacial surgery was already presented [1]. This protocol includes several important steps :

- Simulation of bone osteotomies on a virtual 3D model of the patient skull,
- Planning of the bone segment repositioning, with six degrees of freedom, using a 3D cephalometric analysis,
- Quantitative measurement of the dental occlusion,
- Prediction of the patient facial soft tissues deformations,

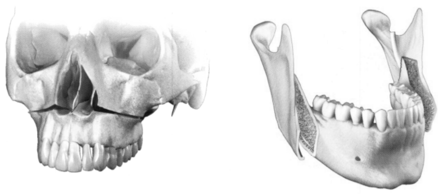

Fig. 1 : Maxillar and mandibular osteotomies

- Computer-aided intervention in the operating room thanks to the 3D bone repositioning planning.

To predict the soft tissues modifications resulting from the repositioning of the underlying bone structures, a finite element model of the face soft tissues has been developed. It is based on a generic mesh composed of several types of nodes : external nodes modelling the skin, intermediate nodes delimiting the dermis and the hypodermis and internal nodes mainly located on the skull (Fig. 2). The generic model is conformed to the patient morphology using the Octree Spline elastic registration method [6]. The skin and skull surfaces of the patient are segmented from the CT-scanner exam. The initial position of the generic model is determined manually. Both generic model and patient surfaces are considered as clouds of points by the registration process. A first elastic registration is effected to match external nodes of the generic mesh to the patient skin surface. The obtained transformation is applied to all nodes of the generic model. A second elastic registration is computed to match the internal nodes in contact with the skull to the patient skull surface. At this stage, some manual adaptation can be effected if the generic model do not match exactly the patient one. Moreover, the transformed generic mesh is corrected in order to fulfill regularity criteria needed for finite element computation.

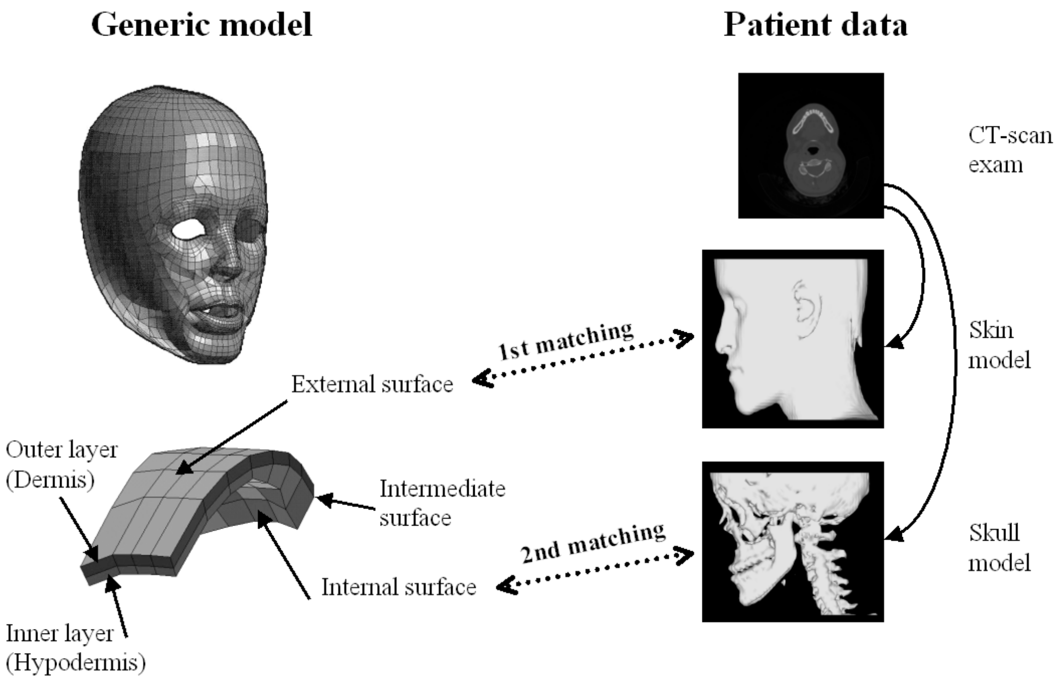

Fig. 2 : Adaptation of the finite element generic model to the patient

OBJECTIVES

The generic face model adaptation method described above works pretty well in many cases but several disadvantages have been identified :

- The initial position of the generic model is performed by manual interaction, which can lead to significantly different registration results, according to the skill of the user.
- The patient skin surface obtained from the CT-scanner exam is built by the Marching Cube algorithm and includes consequently internal structures of the skin (sinus, trachea…). This can disturb in many cases the registration process (the skin surface of the generic model is often matched on the sinus surface of the patient model, for example). The same problem occurs also with the skull surface. This is due to the point-to-point registration process that does not consider the models as "real surfaces" but only as clouds of points.

This paper presents a new approach to perform accurate automatic face registration, based on multimodal data including cephalometric analysis and surface information.

METHODS

1. Determination of an initial position

The first objective is to automatically determine an initial position for the generic model. To perform this task, we propose to use cephalometric data. They consist in a series of particular anatomical landmarks, easily identifiable and defined in 3D on the CT-scanner exam of the patient. The surgeon can perform cephalometric analysis [2,4], based on planes, angles, surfaces or volumes defined from these anatomic points (Fig. 3). For the generic model, these landmarks are defined once for all. It implies that two clouds of corresponding cephalometric points are available in patient and generic models.

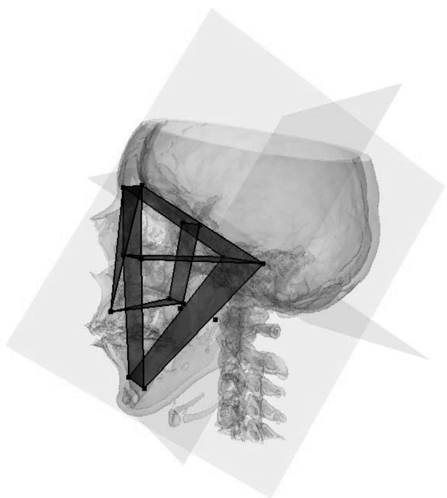

Fig. 3 : Three-dimensional cephalometric analysis based on a series of anatomical landmarks

Our first idea was to compute an initial position by rigid registration of these corresponding points. However, patients suffering from maxillofacial dismorphosis present very different skull morphologies and even after this step the generic model can be located relatively far from the patient one. Therefore, we have preferred to use the elastic registration introduced by [6] to match the two clouds of corresponding points. This does not need much more time and the resulting transformed generic model corresponds better to the patient (Fig. 4).

computed thanks to the adjacent triangles. Then the search for a corresponding target point can be effected according to a double criterion : minimum Euclidian distance and near

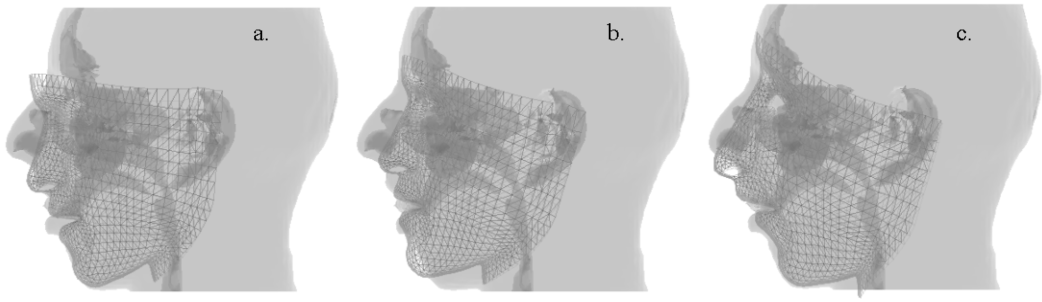

Fig. 4 : Automatic determination of the initial position based on feature points – a. Original position (scanner dependant); b. After rigid registration; c. After elastic registration. The generic model is in wireframe.

2. Surface matching

The second objective concerns the integration of surface information into the elastic registration process. The Octree Spline elastic registration algorithm computes a transformation that minimizes an energy function which represents a weighted sum of distances squares. To calculate these distances, a corresponding point located on the target model (patient) has to be determined for each point of the source model (generic mesh). The point-to-point registration process searches for corresponding points among nodes of the target model. Two improvements can be added to this method.
The first one consists in taking into account the relative local orientation of the surfaces to match [3,5]. For each model node, the external normal can be

normal orientation (i.e. normal scalar product near to one). The corresponding point is searched only in an isotropic neighbourhood centred on the considered source point. A new composed distance $Dist_{Comp}(P, Q)$ is therefore defined between two points P and Q :

$$Dist_{Comp}(P, Q) = Dist_{Eucl}(P, Q) + w \cdot R \cdot (1 - N_P \cdot N_Q)/2$$

$Dist_{Eucl}$ represents the standard Euclidian distance. N_P and N_Q are the normals associated to the points P and Q; w is the weighting factor of the normal orientation term and R is the radius of the isotropic neighbourhood. Note that the scalar product is rescaled between 0 and 1 in order to be high when orientations are discordant and null when normals are oriented identically. Since the first term of

Dist $_{Comp}$ is limited by R, putting w to 1 corresponds to balance both the distance and orientation terms equivalently.
Of course, if the source and target model are locally separated by a distance higher than R, the algorithm will not provide the good corresponding points in these zone. In our case, this situation does not occur thanks to the previous automatic computation of the source model initial position.

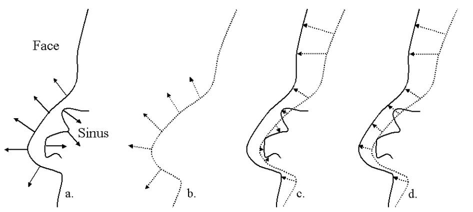

Fig. 5 : Utility of using surface normals – a. Target model; b. Source model; c. Matching by smallest Euclidian distance; d. Using distances and normals.

The orientation of both source and target models surfaces is thus taken into account (Fig. 5), which allows to match the surfaces more efficiently : source points are coupled with target points that correspond better anatomically.
The second improvement is to search corresponding target points on the whole target surface and not only among target model nodes. This task is done in two steps : in a first time, the corresponding target node is determined thanks to the composed distance; in a second time, the closest corresponding point (using the composed distance) is searched in all the adjacent triangles of the previous node by recursive subdivision of each triangle.

RESULTS

Our method has been tested and validated on a set of 10 patients faces.
The improvements of our work have been quantified by measuring distance parameters (maximum, mean, median, standard deviation and 95th percentile) for both methods : point-to-point matching (PPM) using only distance criterion and point-to-surface matching (PSM) using normals information besides.
Subdivision level of the octree was limited to 5 because higher levels require too many computing resources. However, the matching result can be still improved after only one process. Therefore, two successive registration processes have been effected. The profit becomes negligible afterwards.
Several zones of the generic model are not present on the patient data, depending on how the CT-scanner was done (face, neck, end of the nose…). In the same way, ears are not represented in our generic model but appear in the patient model. These zones, where no matching is possible for lack of data, have been removed manually and are not taken into account in the distance measurements (Fig. 6).
Colour distance maps represent the distance between patient and generic model surfaces in order to evaluate locally the matching quality and to identify the possible problem zones (Fig. 7A and 7B).

We have observed that the matching is particularly difficult in the lips region, where surface orientation can considerably vary from one person to

Patient	Matching	Maximum	Mean	Median	Stand Dev	Percentile 95
1	PSM	2,79	0,47	0,37	0,40	1,24
	PPM	6,40	0,51	0,36	0,61	1,38
2	PSM	3,32	0,55	0,46	0,44	1,36
	PPM	3,96	0,56	0,45	0,49	1,53
3	PSM	3,57	0,52	0,39	0,47	1,41
	PPM	7,21	0,69	0,47	0,72	2,23
4	PSM	1,97	0,37	0,28	0,32	0,99
	PPM	2,74	0,42	0,29	0,39	1,23
5	PSM	4,84	0,39	0,29	0,39	1,08
	PPM	2,75	0,44	0,33	0,39	1,23
6	PSM	3,93	0,41	0,30	0,42	1,07
	PPM	4,96	0,65	0,49	0,62	1,78
7	PSM	3,07	0,49	0,39	0,42	1,37
	PPM	3,33	0,54	0,40	0,49	1,54
8	PSM	2,92	0,54	0,42	0,44	1,45
	PPM	4,69	0,60	0,45	0,55	1,68
9	PSM	2,92	0,51	0,43	0,41	1,33
	PPM	5,09	0,61	0,47	0,54	1,72
10	PSM	2,36	0,31	0,24	0,29	0,90
	PPM	1,93	0,36	0,28	0,32	0,99
Average	**PSM**	**3,17**	**0,46**	**0,36**	**0,40**	**1,22**
	PPM	**4,31**	**0,54**	**0,40**	**0,51**	**1,53**

Fig. 6 : Quantitative comparison between PSM and PPM algorithms (error distances are in mm)

another. The largest errors are often located in this area.

It can also be noticed that with the PSM algorithm, the source model does not remain attached to the internal structures of the patient model (interior of the nose, sinus…).

Several of our patients have orthodontic braces or teeth fillings which generate CT-scanner image and 3D surface artefacts but our matching technique remains robust.

The time needed to proceed to one matching process is about one minute on Pentium IV 1.6Ghz PC computer, which is clinically acceptable.

CONCLUSION

The multimodal elastic registration algorithm presented in this paper has been validated to match a generic model of the face to several patients. This method is automatic, precise and robust. The computing time is compatible with clinical practice constraints.

Future work includes mesh regularity verification in order to insure finite element computation feasibility. It will then be possible to simulate soft tissue deformations resulting from bone repositioning during maxillofacial surgery.

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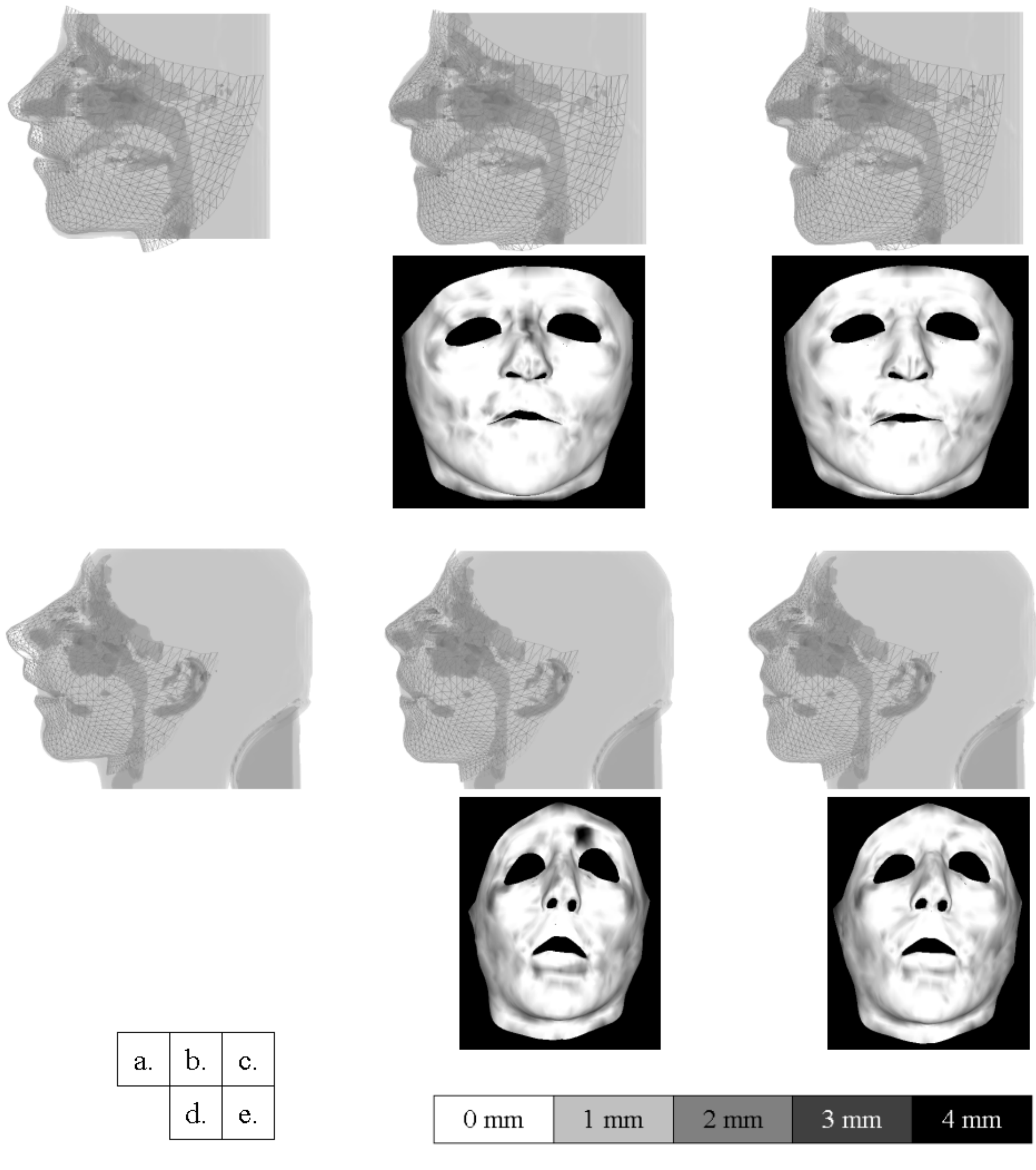

Fig. 7A : Qualitative comparison between PSM and PPM algorithms – a. Initial situation; b. After two PPM processes; c. After two PSM processes; d. Errors distances map corresponding to the PPM final process; e. Errors distances map corresponding to the PSM final process

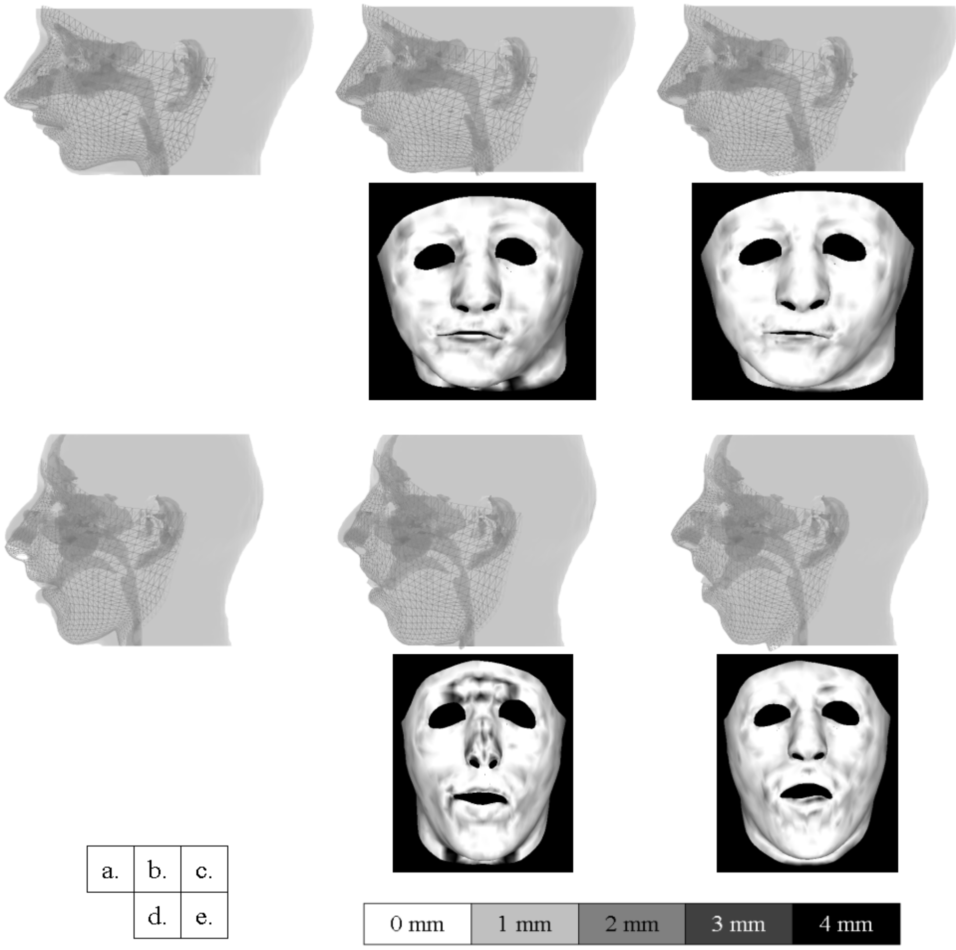

Fig. 7B : see Fig. 7A for détails

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